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High-resolution assessment of environmental benefits of dockless bike-sharing systems based on transaction data

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ABSTRACT

Dockless bike-sharing systems (DLBS) have gained much popularity due to their environmentally friendly features. This study puts forward a distinctive framework for assessing the environmental influences of DLBS in high resolution based on DLBS transaction data. The proposed framework firstly estimates the transport mode substituted by DLBS for each recorded bike-sharing trip by utilizing the route planning techniques of online maps and a well-calibrated discrete choice model. Afterward, greenhouse gases (GHG) emission reductions in every recorded DLBS trip are quantified using Life Cycle Analysis. The proposed framework is applied to an empirical dataset from Shanghai, China. The empirical results reveal that the substitution rates of DLBS to different transport modes have substantial spatio-temporal variances and depend strongly on travel contexts, highlighting the necessity of analyzing the environmental impacts of DLBS at the trip level. Moreover, each DLBS trip is estimated to save an average 80.77 g CO_2-eq GHG emissions versus than the situations without DLBS in Shanghai. The annual reduced GHG emissions from DLBS are estimated to be 117 kt CO_2-eq, which is substantial and equals to the yearly GHG emissions of over 25,000 typical gasoline passenger vehicles. Additionally, the associations among built environments and GHG emission reductions from DLBS are quantitatively investigated to shed light on the spatial variances in the environmental impacts of DLBS. The results can efficiently support the benefit-cost analysis, planning, and management of DLBS.

1. Introduction

The commitments to reducing greenhouse gas (GHG) emissions drive policymakers to leverage alternative and emerging techniques to reduce emissions from all fields. The transport sector, as one of the main contributors to GHG emissions, has high potentials for reducing GHG emissions through technology adoption, such as shared mobility and electrification (Borowski, 2020; Xu et al., 2020; Jin et al., 2015). In recent years, the bike-sharing system (BSS), as a low-budget alternative and environmentally friendly travel choice, has been welcomed by the municipal governments (Chen et al., 2020c; Guo and He, 2020; Gao et al.). BSS started as docked BSS with fixed renting and returning stations, and gradually changed to be dockless with enhanced flexibility and convenience (Chen et al., 2020b; Li et al., 2020b). Dockless bike-sharing systems (DLBS) are currently more prevalent than docked BSS due to their flexibility (Ma et al., 2020a). Although the potential environmental benefit is one of the most critical motivations of developing DLBS in the era of climate change, very few studies have quantitatively evaluated the environmental benefits of DLBS. However, quantitative assessments on the potential benefits derived from DLBS are crucial evidence and supports urban managers to make development decisions concerning DLBS (Barbour et al., 2019; Zhang and Mi, 2018).

The GHG emission reduction of a trip using DLBS is the difference between the GHG emissions of using DLBS and using other transport modes if DBLS were not available for the same trip. Whether (or how much) DLBS produce environmental benefits depends on the transport mode substituted by DLBS (i.e., the transport mode chosen for the trip if the DBLS were not available) and travel characteristics (e.g., distance). Therefore, the key to quantifying the environmental influences of DLBS is to estimate how the DLBS replaces other transport modes (such as walking, transit, and taxis) in various travel contexts. If a traveler uses DLBS for a trip instead of a taxi or private

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Nomenclature

BSS	Bike-sharing service
DLBS	Dockless bike-sharing service
GHG	Greenhouse gas
AZ	Analysis zone
API	Application programming interface
LCA	Life cycle analysis
POI	Point of interest
PD	Population density
ED	Employment density
CLUR	Commercial land use ratio
LLUR	Living land use ratio
PMSLUR	Public management and service land use ratio
PSLUR	Park and square land use ratio
ILUR	Industry land use ratio
MELD	Mixture entropy of land use
MD	Motorway road density
MRD	Motorized road density
BRD	Branch road density
BLD	Bicycle lane density
LFD	Leisure facility density
EFD	Education facility density
PSD	Park and square density
ARMetro	Metro station influence area ratio
ARBus	Bus station influence area ratio

car, it is, without a doubt, beneficial for reducing energy consumption and GHG emissions for the trip. Nonetheless, a bike-sharing trip replacing walking does not create an extra environmental benefit on account of the energy consumption and emissions in manufacturing the bikes and operating DLBS. To obtain substitution rates of BSS to other transport modes, the existing study generally adopted surveys via asking questions such as "What transport mode would you choose for the last trip that you used bike-sharing system if the bike-sharing system were not to exist" (Fishman et al., 2014). The average substitution rates of BSS to other transport modes (e.g., car, walking, and public transit) reported by limited respondents were assumed as the probabilities of BSS replacing the transport mode for all trips of using BSS (Fishman et al., 2014; Anderson, 2015). Then, the surveyed substitution rates were used for assessing the environmental benefits of BSS. Apparently, such methods are inaccurate and would lead to noticeable biases in evaluating the environmental influences of BSS. The substitution rates from limited-sample surveys could merely represent the substitution rates of BSS to other transport modes very coarsely. What transport mode a bike-sharing trip replaces is highly related to the trip contexts in terms of departure time (e.g., morning, noon, or midnight), trip distance, available options, and attributes of available options between origin and destination, transit and road networks. For instance, a trip using DLBS in suburban areas with few public transit services has a high probability of replacing a private car or taxi trip since the travelers have no comparable transit options compared to the urban core. However, if the same trip happens in central business areas, it has a high probability of replacing a trip of using buses or trams due to the convenience of using transits in the central urban areas. Therefore, the substitution rate of a bike-sharing trip to different transport modes should be trip-specific and significantly influenced by the specific contexts of the trip. However, it is very challenging to estimate the substituted transport mode by DLBS and to quantify the environmental influences of DLBS at the trip level. The travel contexts across different bike-sharing trips, such as the origin, destination, start time, road and transit networks, are substantially divergent in both spatial and temporal dimensions. These factors significantly influence the substituted transport mode by a bike-sharing trip and thus the reduced GHG emission due to a bike-sharing trip. As far as we are concerned, there is no existing study that assesses the environmental impacts of DLBS at the trip level with full considerations of the specific travel contexts of every single DLBS trip based on massive transaction data.

To fill the above-mentioned gap, this study develops a novel framework for assessing the environmental impacts of DLBS at a high resolution based on transaction data. The proposed framework first estimates the transport mode substituted by every DLBS trip and calculates the reduced GHG emission due to every trip at the microscope level. More specially, the detailed trip information (e.g., travel cost, distance, and time) of a bike-sharing trip and other possible transport modes for the trip is acquired utilizing the advanced online multi-mode routing techniques and transaction records of DLBS. These provide accurate and realistic options that a traveler could choose if the DLBS were not to exist, as per the specific travel contexts of every single DLBS trip. Based on the above-obtained information, a discrete choice model is employed to estimate the substituted transport mode by DLBS for every single DLBS trip. The reduced GHG emission of each DLBS trip is quantified by a Life Cycle Analysis model. This is, to our best knowledge, the pioneering study to assess the environmental impacts of DLBS at trip resolution with full considerations of detailed travel contexts of every trip. At the macroscopic level, the aggregated GHG emission reductions due to DLBS are estimated based on massive recorded transaction data by DLBS. Taking advantage of high-resolution results, we quantitatively investigate the differences in the environmental benefits of DLBS in different urban areas and the potential effects of the built environment via linear regressions, which have not been investigated in the existing literature. We apply the proposed method to the DLBS in Shanghai for an empirical analysis. The outcomes support urban planners and bike-sharing operators with quantitative evidence of the environmental benefits from DLBS, which are crucial for the cost-benefit analysis and policy-making about DLBS.

The following part of this paper is structured as follows. Section 2 presents a review concerning relevant literature and discusses the research gaps. Section 3 introduces the used data in the empirical analysis of this study. Section 4 provides the details regarding the proposed framework, model formulations, and analysis process. Section 5 gives the results accompanied by discussions, followed by the conclusions and limitations in Section 6.

2. Literature review

Although many qualitative comments on the environmental influences of BSS, few studies have quantitatively evaluated the environmental influences of BSS. Fishman et al. (2014) conducted one of the pioneering studies to quantitatively evaluate the benefits of BSS. They surveyed the substitution rates of docked BSS to car usage in five cities (Melbourne, Brisbane, Washington D.C., London, and Minnesota). The average substitution rate of BSS to the car from the surveys was used as the probability of BSS replacing the car for all trips of using BSS. Then, they approximately calculated the reduction in vehicle kilometers traveled from using private cars due to the introduction of BSS. However, the survey mainly covered limited registered annual members (i.e., sample biases). More importantly, they assumed that the probability of a bike-sharing trip replacing car usage was the same for all trips, which would result in substantial biases (Kou et al., 2020). Anderson (2015) evaluated the impacts of a bicycle-sharing program in Portland and pointed out that the proposed bike-sharing system could reduce air pollution and promote users' physical activities. Nonetheless, the evaluation was based on arbitrary assumptions about the substituted transport modes by bike-sharing systems. These deficiencies caused notable biases in assessing the environmental influences of BSS. Qiu and He (2018) assessed the changes in energy consumption and gas emission brought by BSS in Beijing and concluded the positive influences of BSS on reducing energy consumption and emissions. However, their evaluation method had the same issues as Anderson (2015). The above studies applied the average percentage of BSS trips substituting a transport mode (i.e., car) from limited-sample surveys as the substitution rate of BSS to the transport mode for all other tours of using BSS. Such an assumption is apparently biased. The evaluation of the environmental influences of BSS based on this assumption would be severely biased. As aforementioned, the substituted transport modes by a bike-sharing trip is highly associated with the travel contexts of the trip, including departure time, origin, destination, road, and transit networks (Abdulrazzaq et al., 2020; Yuniar et al., 2020; Kou et al., 2020). To accurately evaluate the environmental influences of bike-sharing systems, it is indispensable to estimate the substituted transport mode by BSS at the trip level, namely for every single trip.

Zhang and Mi (2018) conducted an empirical evaluation regarding the environmental benefits of DLBS in Shanghai using trip-based estimation based on a dataset in 2016. They assumed that a bike-sharing trip could only replace walking or taxis for the trip. If the trip distance of using DLBS was longer than 1 km, the trip was deemed to replace a taxi trip, otherwise replace walking trip. The emission of using a taxi was approximated by trip distance and emission factors. The results of all recorded were aggregated to calculate the overall environmental benefits of DLBS. The unrealistic assumptions about the substitution rates of DLBS to other transport modes were the main issues of the study. For instance, many BSS trips were replacing public transits, rather than a taxi or walk (Ma et al., 2020b; Shaheen et al., 2013; Kou et al., 2020); travelers may choose to walk for a trip over 1 km Kou et al. (2020) proposed an approach for evaluating GHG emission reduction from docked BSS in USA. They estimated the substituted transport mode of a bike-sharing trip considering the trip distance, departure time, and the availability of the public transit near bike-sharing stations. The availability of a public transit for a trip was surrogated by the number of public transit facilities within a 200 m buffer around the origin. They collected the relationships between the probability using different transport modes with trip distance, departure time, and purposes from household surveys. Using the statistics, they assumed the probabilities of a bike-sharing trip replacing different transport modes and empirically analyzed the influences of docked BSS on reducing GHG emissions. Without a doubt, Kou et al. (2020) made an improvement as compared to the previous literature. Nevertheless, Kou et al. (2020) did not adequately address the main issues in assessing the environmental influences of DLBS and had three critical limitations: 1) What matters in mode choice is not the attribute of an option, but the superiority or inferiority of the option as compared to other competing options. In mode choice, travelers select the option with the highest subjective utility via trade-offs among attributes (e.g., cost and time) of available options. 2) Whether a traveler could choose public transits (e.g., bus and metro) to a destination depends on whether a transit route to the destination exists, rather than where there are transit stations near the origin. If there are transit stations but no transit route (or long detour) to the destination, the traveler will not use transits for the trip. 3) Two bike-sharing trips with the same trip distance, departure time, and purpose may replace different transport modes. For instance, one DLBS trip happening in a suburb area with few transit services is more likely to substitute taxis, as compared to the same trip in central areas with convenient transit systems. Due to the mentioned limitations, the approach in Kou et al. (2020) still can not accurately estimate the substituted transport mode by DLBS in each trip and thus accurately evaluate the environmental influences of DLBS.

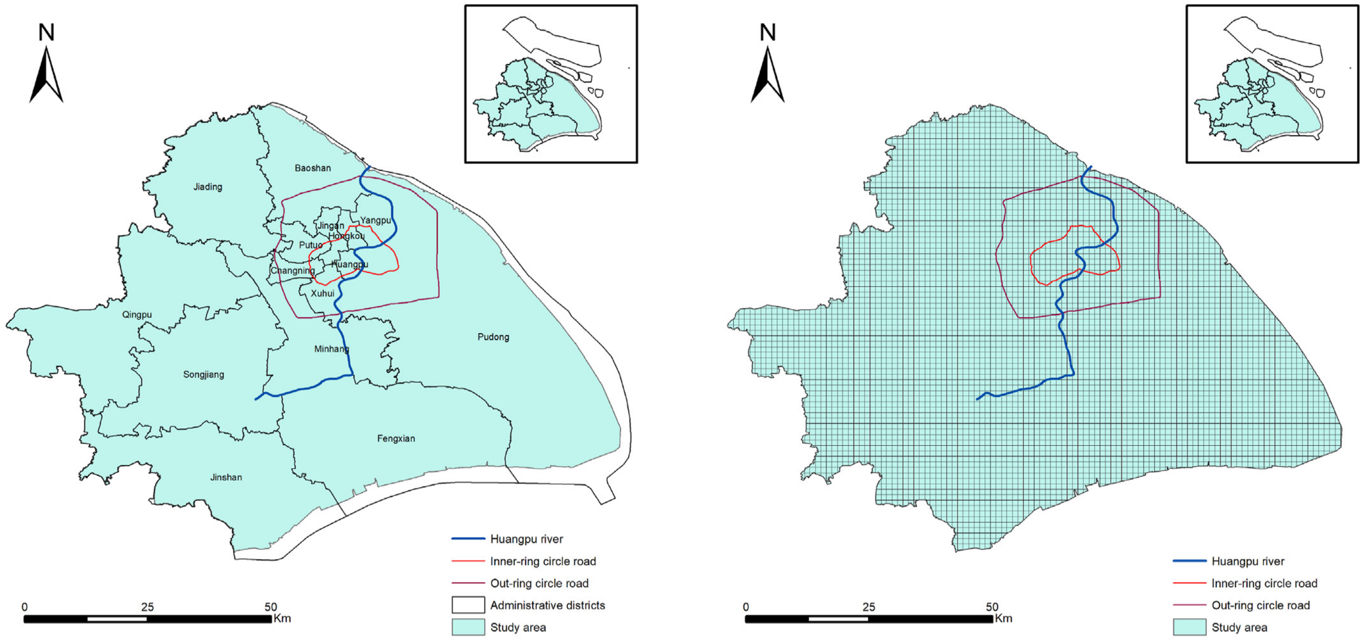
The core of evaluating the environmental influences of DLBS is accurately estimating what transport modes a bike-sharing trip replaces in a specific travel context. The key is to obtain the attributes of available options besides DLBS and predict the travelers' choices in the specific travel contexts for every single trip. Ideally, the investigators could ask each user after a bike-sharing trip about what transport he/she would use if there were no DLBS. However, it is not feasible and practical to collect such data in reality. To address the above research gaps, this study presents a novel methodology for assessing the environmental influences of DLBS based on an improved estimation of the substituted modes at the trip level. In more detail, we leverage the multi-mode routing technique of online navigators to accurately acquire detailed information of other alternative transport modes besides DLBS in the real transport network for the same origin, destination, and depart time of a recorded bike-sharing trip. Afterward, we utilize a travel choice model to estimate the chosen transport mode by the traveler for finishing the trip if the DLBS were not available (i.e., the substituted transport mode by DLBS). Simultaneously, we quantify the reduced GHG emission from each DLBS trip based on Life Cycle Analysis. The proposed method realizes the assessment of environmental analysis of DLBS at the resolution of trip level, which is the pioneering study to achieve such a high-resolution assessment. The proposed approach is used for an empirical analysis concerning DLBS in Shanghai of China.

Moreover, the existing work merely assessed the environmental influences from a global and aggregated perspective due to the fact that their methods could merely obtain results in a coarse resolution (e.g., approximation at the overall level). The spatial heterogeneity in the environmental effects of DLBS and its associations with built environments lack deep investigations to support the planning and management of DLBS in different urban contexts effectively. The built environment factors such as land use characteristics, road, and transit infrastructure, are expected to influence travel behavior (Fishman et al., 2014; Sun et al., 2018; Gangeraj et al., 2017; Wu et al., 2020) and thus affect the substituted modes of DLBS and GHG emission reductions from DLBS. Making the best of the trip-level analysis in the proposed approach and available data, we also quantitatively investigate the potential influences of built environment factors on the environmental influences of DLBS to support the management and planning of DLBS in different urban contexts.

3. Study areas and used transaction data of DLBS

3.1. Study area

The study area is Shanghai of China, as shown in Fig. 1a. Shanghai is one of the largest metropolises in China, which has a population of 24.24 million and an area of 6341 km^2 by the end of 2018. In 2018, the gross domestic product reached 3.268 trillion Chinese Yuan, accounting for 6.6% of the total Chinese gross domestic product. The municipal area of Shanghai consists of 16 districts. The study area contains various urban contexts, including urban regions, suburban regions, rural areas, and rural-urban continuum. The central area of the city includes seven districts,



(a) Administrative division of Shanghai

(b) The partitioned zones

Fig. 1. The study area and partitioned zones for analysis.

including Huangpu, Xuhui, Changning, Jian'an, Putuo, Hongkou, and Yangpu, most parts of which are within the inner-ring circle road (i.e., the red circle in Fig. 1a). The areas outside the out-ring circle (i.e., the purple circle in Fig. 1a) are rural areas. Chongming district is an island area with few inhabitants and many undeveloped regions such as forests and wetlands. On account of few DLBS trips in the Chongming district, we exclude it in analysis in case of biases. The study area is divided into a grid with 0.01 longitude × 0.01 latitude rectangles (Fig. 1b). Each rectangle is treated as an analysis zone in this study.

3.2. Used transaction data of DLBS

This study utilizes the DLBS transaction data provided by Mobike, which is one of the largest DLBS operators in China. The used data covers 14 consecutive days from August 26th to September 8th in 2018, and contains more than 27 million trips recorded by 635,833 operating sharing bikes in Shanghai. The data includes all operating Mobike bikes in Shanghai over the recorded period and describes over 40% of the market share of bike-sharing systems in Shanghai in 2018 (iiMedia Research, 2018). Such a large number of transaction records guarantee the representativeness of data used to reflect the DLBS in Shanghai and the feasibility of using the data for empirical analysis in Shanghai. Each transaction record contains a unique trip ID, bike ID, timestamps, and coordinates of the starting and ending locations.

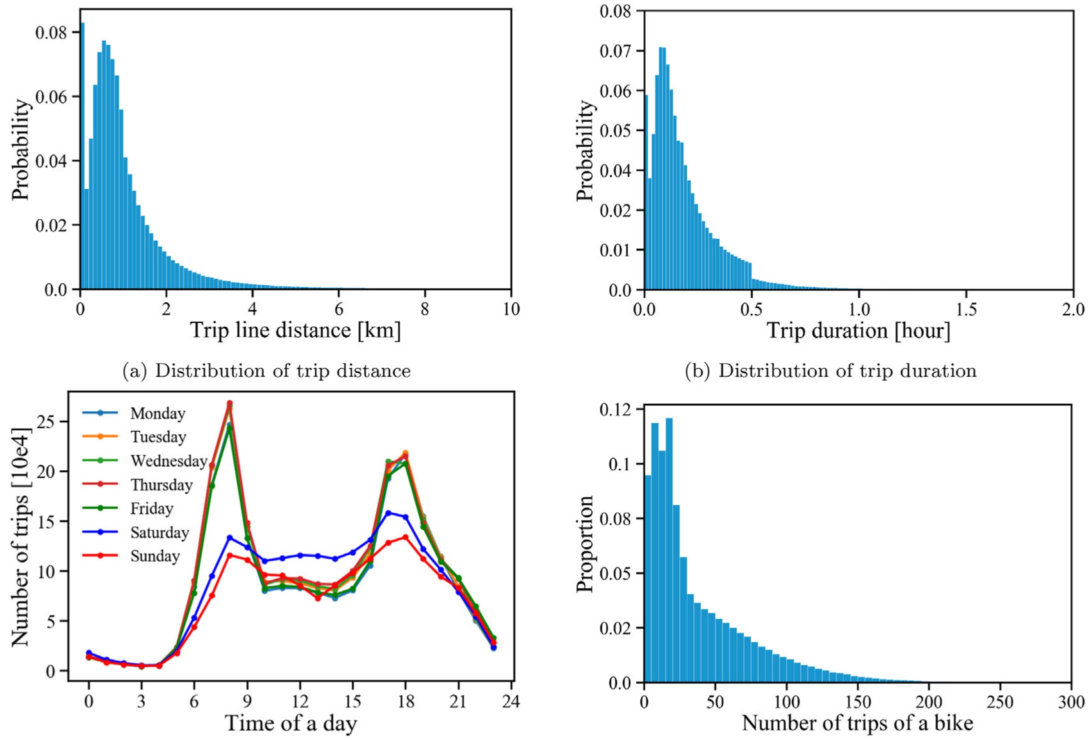
We filter out trips whose starting or ending locations are outside the study area. However, there are still some abnormal values in terms of trip duration and distance due to technical errors (e.g., GPS positioning error) or unusual user behavior. Hence, a data cleaning process is executed to filtrate potential outliers. The trip records with abnormal distance or duration are excluded. Fig. 2a and b demonstrate the statistical distributions of trip distance and duration, respectively. We remove trips with a trip distance (i.e., the Euclidean distance between two points) shorter than 100 m or longer than 10 *km*, and a trip duration less than 60 s. Such records are likely to be faulty records due to technical errors or unusual user behavior. We selected the 10 km as the threshold as it is the 99% quantile of the trip distance distributions based on our data, as displayed in Fig. 2a. After cleaning, more than 23 million trips from 617,249 bikes remain and are used for the final analysis.

From the statistical levels, most DLBS trips are shorter than 5 km and half an hour (Fig. 2a and b). The mean trip distance and duration are 1105 m and 11.7 min, respectively. The statistical results in our study are in accordance with the findings in the relevant literature (Li et al., 2020c; Kou et al., 2020). Fig. 2c shows the temporal distribution of bike-sharing trips across a day in Shanghai. The distributions across workdays (from Monday to Friday) are very similar. They have two pronounced peaks in the morning (7–9 AM) and evening (5–7 PM), which indicate the typical commuting patterns on workdays. Evident differences are observed between the temporal distributions of workdays and weekends. The morning and evening peaks are not apparent on weekends. Fig. 2d shows the distribution of the usage frequency of the bikes. Most bikes during the studied period are used less than 50 times. The average daily usage frequency of a bike is 2.69 times.

4. Analysis framework and methodology

4.1. Methodological framework

The core of assessing the environmental influences of DLBS is to decipher what transport mode every single bike-sharing trip replaces and then compare the emissions of using DLBS and using transport modes if DLBS were not to exit. More specifically, we need to know what transport mode the traveler would use for a recorded bike-sharing trip if the DLBS were not to exist. By comparing the emissions of using other transport modes in contrast to DLBS, the reduced emission due to using DLBS can thus be quantified. The environmental benefit of DLBS can be defined as the sum of emission reductions of all trips using DLBS. Fig. 3 demonstrates the outlines of the proposed framework. The proposed framework



(a) Distribution of trip distance (b) Distribution of trip duration

(c) Temporal distribution of bike trips (d) Distribution of usage frequency per bike

Fig. 2. Descriptive analysis of bike-sharing transaction data. Fig. 2a and b describe the distribution of trip distance and trip duration of the data within the study area. Fig. 2c and d are for the data after removing trips with anomalous distance or duration.

contains three main components, including the trip-specific information extraction, trip-specific mode substitution estimation, and assessing GHG emission reductions due to the DLBS.

4.1.1. Acquirement of trip-specific travel contexts using multi-mode routing planning techniques

The first step is to extract the information about other available transport modes besides DLBS for each recorded bike-sharing trip. This task is challenging as the available options for a trip are highly related to travel contexts, including road structure, transit network, and departure time, which display substantial variances in spatial and temporal dimensions. To obtain the available travel choices and their attributes, we utilize the Direction Application Programming Interface (API) for multi-mode routing planning in Amap. Amap is one of the largest online navigator and map companies in China (Amap, 2020). Each DLBS transaction record contains the coordinates of the origin and destination, starting and ending timestamps for each trip. Based on the starting and ending locations as well as the departure time of the trip (i.e., the hour and minutes in a day), the Amap Direction API can output the available travel mode alternatives (e.g., walking, taxi, bus, metro, and bicycling) and their corresponding attributes (e.g., cost, trip duration, trip distance, and route). The pronounced advantage of map API is its capacity to acquire the realistically available options for the same origin, destination and departure time of each bike-sharing trip, with full considerations of real road topology, transit network, and schedules. The outputs from the Amap Direction API are exactly what we get after searching routes in online navigators such as Google Map. The outputs of API are summarized in Table 1. For taxi, walking, and bike, the output information in Table 1 can be used directly. The public transport reports several stages, including the access stage to the starting transit station, in-vehicle stage, and egress stage from the ending station to the destination, as shown in Table 1. For our empirical analysis, we consider the overall trip time (i.e., the sum of travel time in different stages) of using public transit services, as they are the direct factors considered by the travelers in travel decision making.

4.1.2. Trip-specific estimation of substituted mode by DLBS

After obtaining accurate information about the available alternatives for a specific bike-sharing trip, the core is to estimate which transport mode the traveler would choose for the trip if DLBS were not available. We make the best of travel mode choice models to predict the replaced transport mode by DLBS for a bike-sharing trip. Specifically, we employ the Mixed Logit Model to estimate the substituted mode by DLBS. The Mixed Logit Model is a well-known and prevalent technique for modeling travel choice behavior and has been widely employed to predict travelers' choice behavior in terms of route, mode, and departure time choices (Hensher and Greene, 2003). As per microeconomic theories, travelers would make trade-offs among attributes of available alternatives and select the one with maximum subjective utility. The subjective utility U_{jqm} of transport mode j perceived by user q is:

$$U_{jq} = \underbrace{\sum_{k} \beta_{qjk} x_{jk} + ASC_{jq}}_{V_{jq}} + \varepsilon_{jq} \tag{1}$$

where x_{jk} denotes the attribute k of transport mode j, such as travel cost and time for a trip. The β_{qjk} is the coefficient of attribute k and represents the degree that traveler q values the attribute k of transport mode j. ASC_{jq} stands for user q's unobserved predilections towards transport mode j besides the influences of observed attributes. ε_{qj} is the random error term for modeling stochastic in the

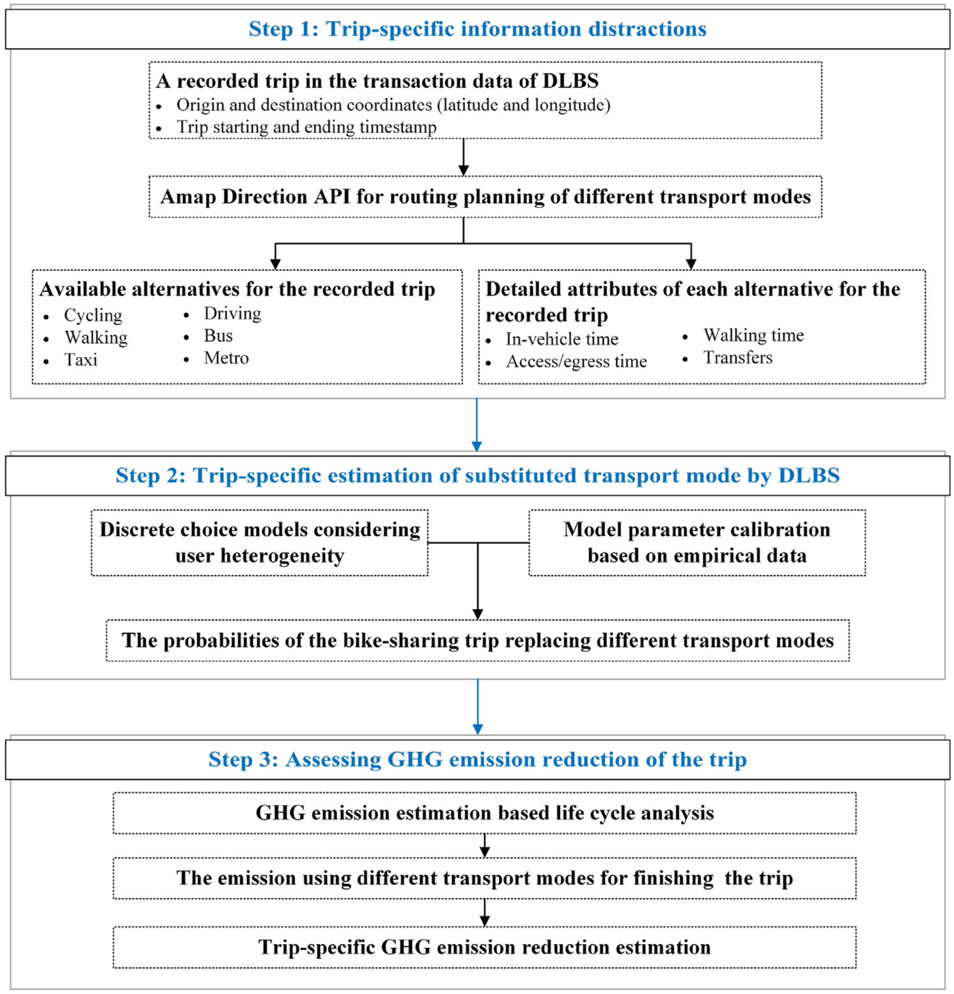


Fig. 3. The propose framework to assess the environmental benefits of DLBS.

Table 1
The trip information obtained from Amap API.

API type	Mode	Information
Walking results	Walking	Walking distance, duration Walking route trajectory
Bike results	Bike	Bike distance, duration Bike route trajectory
Public transit results	Bus, metro	Access distance, duration In-vehicle distance, duration Egress distance, duration Transit distance, duration Ticket cost Transit route trajectory
Driving results	Taxi	Driving distance, duration Cost taxi route trajectory

utility of transport mode j (Greene et al., 2006). Different travelers have distinct weights on the same attribute. For instance, some travelers have a higher value of time than others and attach more weight to travel time. Therefore, we further consider the heterogeneity in preferences among travelers by setting the coefficients in the utility function to be random (Greene et al., 2006; Hensher and Greene, 2003). For simplicity, let $\beta \sim f(\mu_\beta, \varphi_\beta)$ be a representative coefficient in the utility function. μ_β is the mean value of the random coefficient, and φ_β is the parameter denoting variances across different travelers. We set the random coefficients to be truncated normal distributions, which merely keep the 95% confidence intervals of normal distributions (Gao et al., 2018). Assuming that the alternative with the highest subject prospect is preferred, the probability of user q choosing transport mode j in a choice scenario is:

$$
\begin{aligned}
&= \mathbf{Prob}\{U_{jq} \geq U_{yq}\} \\
P_{jq} &= \mathbf{Prob}\{V_{jq} + \varepsilon_{jq} \geq V_{yq} + \varepsilon_{yq}\} \\
&= \mathbf{Prob}\{(V_{jq} - V_{yq} \geq (\varepsilon_{yq} - \varepsilon_{jq}))\}
\end{aligned} \tag{2}
$$

The random error components ε_{jq} are assumed to be identically and independent extreme value distributions (i.e., the Logit model family). Hence, we can obtain

$$
P_{jq} = \int \frac{exp(U_{jq})}{\sum_{y \in \mathbf{Y}} exp(U_{yq})} \mathbf{d}(\boldsymbol{\beta}) \tag{3}
$$

where Y is the set of available options for a user, and β denotes the set containing all the random coefficients to be estimated in the model.

To calibrate the parameters in the choice model, we use a stated preference survey concerning mode choice behavior in Shanghai, which was collected in 2017 (Gao et al., 2020a). The survey firstly asked the respondent about his/her commonly used transport modes for commuting and corresponding attributes (e.g., cost and travel time). The same information concerning available but forgone other alternatives was collected as well to construct a reference preference scenario. Afterward, the respondent is asked to complete stated preference scenarios about mode choices. The scenarios assumed three alternatives with detailed attributes, including travel cost and travel time. The respondents selected the preferred transport mode as per their preferences. More details of the survey design are available in Gao et al. (2020c, a). The used dataset contains 1318 valid respondents. The maximum likelihood method was applied to estimate a joint reference preference and stated preference model referring to Schmid et al. (2019) and Gao et al. (2020a). The calibrated model parameters are summarized in Table 2. The results provide quantitative outcomes about how travelers weigh the attributes of different transport modes. Based on the extracted information about all available options and their attributes in last subsection, the calibrated Mixed Logit Model could predict the probabilities of choosing different transport modes for the trip if there were no DLBS.

Our available data for Mixed Logit Model calibration did not have the walking option, so we could not calibrate the coefficient of walking time and unobserved predilection for walking $ASC_{walking}$. To solve this, we referred to the value of time for walking from the relevant literature (Abrantes and Wardman, 2011; Kamargianni and Polydoropoulou, 2013; Wardman, 2004). We set the coefficient of walking time to be twice as the calibrated coefficient of travel time of bus in the model and $ASC_{Walking}$ to be the same as the bus as reported in the relevant literature. When the trip distance is very small such as 300 m, walking is dominant, and travelers would not consider other choices in most cases. On the basis of statistics about the distributions of the travel distance of different transport modes from the latest transportation investigation report of Shanghai, we set a pruning criterion: if the trip distance of a bike-sharing trip is less than 500 m, it replaces walking; if the trip distance is over 500 m, the calibrated MLM is used to estimate the probabilities of substituting different modes by DLBS. We did not consider that DLBS replaced private cars as we could not know if a private car was available for the recorded trip, and the substitution rates of DLBS to private cars were very low (less than 2%) in Shanghai (Wang, 2019).

4.1.3. Assessing GHG emission reduction of every DLBS trip

The GHG emission reduction of a trip using DLBS is the discrepancy in the GHG emissions of using DLBS and using other transport modes if DBLS were not available for the same trip. The Life Cycle Analysis (LCA) is used to calculate the GHG emissions of using a transport mode for a specific trip. The used LCA considers GHG emissions in the production and operation phases, as suggested by the literature (Wang, 2019; Zhang and Mi, 2018; Kou et al., 2020). An emission factor is a representative value that associates the quantity of GHG emissions of using a transport tool with an activity related to the release of GHG emissions (Chen et al., 2020a). For instance, an emission factor of 150 g carbon dioxide equivalent (CO_2-eq) per km denotes the GHG emissions of using the transport mode per kilometer is 150 g CO_2-eq. On account that walking does not require mobility tools, the emission factor of walking is set to be zero. For other transport modes such as bus, taxi, metro, and bike, the emission factors are obtained by considering the associated GHG emissions in production and operation phases. The GHG emission per passenger-kilometer of a transport mode j from the production phase Ep_j is

$$Ep_j = \frac{Cp_j}{M_j N_j} \tag{4}$$

where Cp_j is the overall GHG emissions from the production of transport mode j, M_j is the mileage life of transport mode j, and N_j is the average passenger number during a trip. The GHG emissions of different transport modes in production stage Cp_j are listed in Table 3. The mileage life refers to the overall driving distance of a transport mode before scrapping. The used mileage lives of different transport modes in Shanghai are listed in Table 3, which are based on statistics in Shanghai Almanac (2017). As for the average passenger in a trip, N_{bus} is calculated by $\frac{APA}{VA \times DT}$ based on the annual passenger amount (APA) in the bus system of Shanghai, the vehicle amount (VA), and the daily trips per vehicle (DT). The same calculation method goes for N_{metro}. The relevant parameters are listed in Table 3. The N_{taxi} is set to be two referring to (Wang, 2019; Zhang and Mi, 2018). In terms of DLBS, N_{bike} is 1 since only one person is allowed to use a sharing bike. The mileage life of a shared bike is measured by its average turnover per year (D), average trip distance (R), and service year (T), i.e., $M_{bike} = D \times R \times T$. D and R are 981.85 and 1579.7 m as per our data, respectively. T is three years

Table 2
The estimated parameter of mode choice model based on the collected behavioral data in Shanghai.

Parameters	Value	Robust Std. Err.	Robust t-test
μ_{cost}	−0.0334*	0.00490	−6.81
φ_{cost}	0.0309*	0.00446	6.93
$\mu_{traveltime\_bus}$	−0.0216*	0.00316	−6.83
$\varphi_{traveltime\_bus}$	−0.0104*	0.00151	−6.91
$\mu_{traveltime\_car}$	−0.0228*	0.00342	−6.66
$\varphi_{traveltime\_car}$	−0.00454*	0.00106	−4.26
$\mu_{traveltime\_metro}$	−0.0150*	0.00243	−6.19
$\varphi_{traveltime\_metro}$	0.00813*	0.00130	6.27
$\mu_{traveltime\_taxi}$	−0.0147*	0.00340	−4.33
$\varphi_{traveltime\_taxi}$	−0.00748*	0.00188	−3.97
Scaling parameter for SP utilities	3.48*	0.506	6.89
Nested effect between metro and bus	0.627*	0.0989	6.34
$ASC_{Car}(RP)$	3.26*	0.227	14.38
$ASC_{Car}(SP)$	0.844*	0.130	6.49
$ASC_{Metro}(RP)$	1.44*	0.174	8.26
$ASC_{Metro}(SP)$	0.173*	0.0473	3.66
ASC_{Taxi}	−0.360*	0.117	−3.08
ASC_{Bus}	0(fixed)#		

Note:
The nested effect between metro and bus is modeled by an error component model (Gao et al., 2020c, a).
*Represents the significance at the confidence level of 99%.
#ASC_{Bus} is always 0 as the reference option.

Table 3
The parameters for calculating production GHG emission.

	Annual mileage (km/year)	Annual passenger amount(p/y)	Vehicle number	Production GHG emission (g CO_2-eq)	Service year	Average passenger per trip
Bus	1.35×10^9 [a]	2.39×10^9 [a]	16693[a]	40,928,300 [b]	8	19.6
Metro	8.43×10^7 [a]	3.40×10^9 [a]	681 [a]	10,656,350 [b]	30	116
Taxi	5.9×10^9 [a]	8.62×10^9 [a]	47271[a]	6,567,200 [b]	6	2 [b]

[a] Shanghai Almanac (2017).
[b] Wang (2019).

according to the industry policy (Cao, 2018).

The GHG emission per kilometer from the operation phase Eo_j is formulated as

$$Eo_j = K_j \theta \tag{5}$$

where K_j is the energy (such as fuel and electric) consumption per kilometer of transport mode j, θ is the parameter relating the energy consumption to corresponding GHG emissions. The GHG emissions during operation of different transport modes in the contexts of Chinese cities are listed in Table 4. The emission of bike-sharing and walking are zero in the operation period because they do not consume energy during operation. The final emission factor for transport mode j (E_j) is the summary of Eo_j and Ep_j.

$$E_j = Ep_j + Eo_j \tag{6}$$

The calculated emission factors are demonstrated in Table 4. The GHG emission factor of using transport mode j for a trip GHG_j is

$$GHG_j = E_j \times Distance_j \tag{7}$$

where $Distance_j$ the travel distance of using transport mode j for a trip. Using public transits such as bus and metro also involves walking, as shown in Table 1. For instance, using bus for a trip includes walking access distance to the starting bus station, taking the bus and egress distance from bus station to the final destination. The GHG emissions of bus trips only consider the GHG emissions from taking the bus because walking does not produce extra emissions.

The discrepancy between the GHG emissions of using the substituted transport mode and using DLBS for a specific trip is regarded as the GHG emission reduction from using DLBS for the trip. For instance, if a DLBS trip replaces a trip using a taxi with a probability p and using a bus with a probability $1 - p$, the GHG emission reduction of the trip is calculated by $p \times GHG_{taxi} + (1 - p) \times GHG_{bus} - GHG_{bike}$.

After obtaining the GHG emission reduction for every single recorded bike-sharing trip, we further calculate the aggregated GHG emission reductions in all partitioned analysis zones (AZs) in Fig. 1b. It is realized by comparing the GHG emissions in two different situations. One is the aggregated GHG emissions in AZs when using DLBS. Another situation is the aggregated GHG emissions using other alternatives if the DLBS were not to exist. For a given AZ, the difference of the aggregated GHG emissions under the two situations is treated as the reduced GHG emissions due to DLBS. For each trajectory, the GHG emission using a transport mode is mapped to the AZs by the following process. Fig. 4 shows an example that a trajectory crosses five AZs (A1, A2, A3, A4, A5). The trajectory is divided into five sub-trajectories, partitioned by the boundaries of AZs. The GHG emission in each crossed AZ is calculated by the distance of sub-trajectory in the AZ multiplying GHG estimation factor of the given transport mode. By mapping, GHG emissions in all the crossed AZs can be calculated for all trajectories of using DLBS and other alternative transport modes for a specific trip. After enumerating the process for all recorded trips, the aggregated GHG emissions under the above two scenarios, as well as corresponding GHG emission reduction due to DLBS, in all AZs could be attained.

Table 4
The calculated emission factors of different transport modes.

Emission factors (g CO_2-eq/km)	Bus	Metro	Taxi	Bike	Walking
Production	3.21	0.15	4.39	7.43	0
Operation	31.38 [a]	22.47 [a]	126.86 [a]	0	0
Total Emission	34.59	22.62	131.25	7.43	0

[a] Wang (2019).

4.2. The associations between built environment factors and the environmental influences of DLBS

In our empirical analysis, we find that the environmental benefits of DLBS differ in different urban contexts. The trip-level analysis in the proposed framework enables us to further investigate the potential reasons for the spatial differences in the environmental benefits of DLBS. Therefore, we investigate the effects of built environment factors on the environmental influences of DLBS to reveal the underlying reasons. We employ the Multiple Linear Regression to examine the potential associations between the quantified environmental benefits of DLBS and built environment factors in AZs. The formula is

$$Y_i = \alpha_0 + \sum_k \alpha_k X_{ki} + \varepsilon_i \tag{8}$$

where Y_i represents the dependent variable, i.e., the daily GHG emission reduction in each AZ; α_k is the coefficient of the independent variable X_{ki}, and ε_i is the residual error. The investigated built environment factors (or explanatory variables) contain the well-known 5-D built environment factors, including density, diversity, design, destination, and distance to transit (Cervero et al., 2009). The definitions of the investigated built environment factors are summarized in Table 5.

These explanatory variables are calculated for each AZ based on

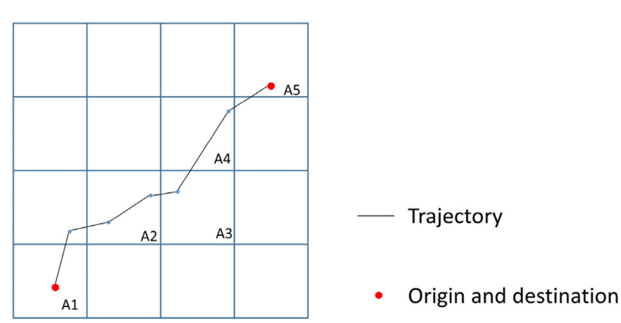


Fig. 4. Example of trip division.

multiple data resources, including Point of Interest (POI) obtained from Amap, GIS information about road networks provided by OpenStreetMap, and population census from the Population Census Data (Gao et al., 2020b). The POI database provides 1,120,924 POIs in the area of Shanghai. Each POI consists of the element name, address, element types, and location (longitude and latitude). The population density in an AZ is obtained from the statistics of Population Census Data. On account that the partitioned zones in Population Census Data were not in line with the divided AZs in this study, we acquire the population density in each AZ as per the overlapping areas between the AZ and Population Census Data surveying zones referring to Gao et al. (2020b). The formulation to calculate the population density in an AZ is

$$PD_i = \sum_{k=1}^{K} \frac{O_{ik}}{S_i} \cdot PD^k \tag{9}$$

where PD_i is the imputed population density of AZ i, S_i is the floor area of AZ i, k is the index for Population Census Data survey zones, PD^k is the population density of k^{th} survey zone from Population Census Data, O_{ik} is the overlapping area of Population Census Data survey zone k and AZ i. The employment density is measured by the density of POIs that can provide jobs, including POIs of commercial service, public management and service. The built environment factors relating to land use characteristics in each AZ is calculated using the POI database. We categorize POIs into six categories of land-use types based on the land use classification standards in China, including commercial land use, living land use, public management, and service land use, industrial land use, road and transport infrastructure land use, and park and square land use. By mapping the POI into the partitioned AZs, the density of different facilities and land use ratios of different categories in each AZ could be calculated. Furthermore, the mixture of land use is also investigated, calculated by the entropy of land use (Li et al., 2020a). As for the built environment factors concerning design, the data about the road network in Shanghai from OpenStreetMap are used. The road densities of different road types are extracted by mapping the road network with the AZs. Concerning factors about transit such as accessibility bus and metro, we utilize the indicators provided in Li et al. (2020a), metro station influence area ratio (ARMetro) and bus station influence area ratio (ARBus). Each transit station serves a certain area (i.e., influence area) instead of a point. The influence area of a transit station, is defined as a buffer area around the transit station. The ARMetro or ARBus is defined as the ratio of the overlapping area of all the transit stations' influence area and the AZ. In terms of the radius of the buffer are for each transit station, we use the average distance of two adjacent transit stations. Here, 158 m and 1025 m are set for measuring the ARMetro or ARBus, respectively.

5. Results

This section firstly presents the analysis results about the substituted transport modes by DLBS in various travel contexts. Afterward, the results of the GHG emission reduction from DLBS in both per-trip and overall levels are analyzed. Lastly, results about relations between GHG emission reductions from DLBS and built environment factors are provided with corresponding discussions.

5.1. The substituted transport modes by DLBS in spatiotemporal dimensions

For each recorded bike-sharing trip, we use tailored choice modeling to estimate the probabilities of using different transport modes if DLBS were not available, named the substitution rate of DLBS to other transport modes. From the statistical perspective,

Table 5
The built environment variables and definitions.

Explanatory variables	Definitions	Unit	Abbreviation
Density			
Population density	Number of residents per unit area	persons/km^2	PD
Employment density	Number of employment positions per unit area	number/km^2	ED
Diversity			
Commercial land use ratio	The floor area of commercial land use divided by the floor space of an AZ	%	CLUR
Living land use ratio	The floor area of the living land use divided by the area of an AZ	%	LLUR
Public management and service land use ratio	The floor area of the public service land use divided by the floor space of an AZ	%	PMSLUR
Park and square land use ratio	The floor area of the park and square land use divided by the floor space of an AZ	%	PSLUR
Industry land use ratio	The floor area of the industrial land use divided by the floor space in each AZ	%	ILUR
Mixture entropy of land use	The land use entropy is an indicator for measuring the degree of land use mix. It is calculated by $pm_i = -\sum p_{i,k} log(p_{i,k})$ where $p_{i,k}$ is the ratio of land use type i		MELD
Design			
Motorway road density	The length of the motorway including the arterial and motorway that not allow bicycling in each AZ	m/km^2	MD
Motorized road density	The length of primary and secondary roads that can be used by bicycles but prioritize motorized vehicles in each AZ	m/km^2	MRD
Branch road density	The length of street, service and living roads in each AZ	m/km^2	BRD
Bicycle lane density	The length of dedicated lanes for bicycles in each AZ	m/km^2	BLD
Destination			
Leisure facility density	The density of leisure facilities, and calculated by the number of POI for each AZ	number/km^2	LFD
Education facility density	The density of education-related facilities and calculated by the number of POIs belonging to the category of school and education institutions for each AZ	number/km^2	EFD
Park and square density	The density of park and square, and calculated by the number of POIs belonging to the category for each AZ	number/km^2	PSD
Transit			
Metro station influence area ratio	The ratio of the overlapping area of influence area of all the metro stations and the AZ. The influencing area of a metro station is defined as a buffer area with a radius of 1025 m around the metro station.	%	ARMetro
Bus station influence area ratio	The ratio of the overlapping area of influence area of all the bus stations and the AZ. The influencing area of a bus station is defined as a buffer area with a radius of 158 m around the bus station	%	ARBus

30.7% of the trips using DLBS are replaced by walking as per our empirical analysis. It is logical as DLBS mainly serves for short-distance trips and many DLBS trips are less than 500 *m*. Therefore, DLBS is a significant competitor of walking. The results indicate that 32.0%, 18.7%, and 18.6% of trips using DLBS would be substituted by bus, metro, and taxi, respectively, if DLBS were not available. The estimated substitution rates of DLBS to different transport modes in our study are in accordance with the empirical findings based on surveys in Shanghai reported by Wang (2019). However, we suppose that our estimated results are more robust as we utilize over 20 million data points and Wang (2019) merely surveyed less than 1000 respondents.

It is found that the average substitution rates of different transport modes to DLBS are not homogeneous in both spatial and temporal dimensions. Fig. 5 displays the estimated substitution rates of DLBS to other transport modes in different trip distances. The trip distance (i.e., riding distance by DLBS) is categorized with an interval of 500 *m*. It can be observed from Fig. 5 that the substation rate of DLBS to a certain transport mode is related to the trip distance. The average substitution rate of DLBS to walking decreases sharply with trip distance. When the trip distance is over 3 *km*, the substitution rate for walking is nearly zero. This conforms to the reality as passengers hardly adopt walking for long-distance trips. The substitution rate of DLBS to taxi displays a declining trend with increasing trip distance. However, the substitution rate to bus increases with trip distance, which reaches a peak at around 2 *km* and then decreases with trip distance. The ratio of DLBS replacing the metro is very low when the trip distance is less than 1.5 *km*. This may be ascribed to the fact that the distance between two metro stations in Shanghai is generally around 1.5 *km* and even larger in suburban areas. Therefore, it is unnecessary to adopt the metro for trips below 1.5 *km*, which is the reason for the nearly zero substitution rate of DLBS to the metro for trips with a distance of fewer than 1.5 *km*. The substitution rate to metro increases with trip distances over 2 *km*.

Fig. 6 demonstrates the substitution rates of DLBS to other transport modes in different periods of a day. The probabilities of DLBS replacing metro and bus from 0:00 to 5:00 a.m. are zero, which are ascribed to the fact that the bus and metro systems are closed after around 23:00 p.m. and open around 5:30 a.m. in Shanghai. Therefore, DLBS is very likely to replace taxi and walking during midnight. The substitution rates of DLBS to metro and bus around commuting peak hours (6:00 a.m. to 9:00 a.m. and 17:00 p.m. to 19:00 p.m.) are relatively larger as compared to other periods, which may be ascribed to the fact that many travelers in Shanghai used DLBS in these periods for commuting instead of public transits or connecting to public transits. The median substitution rate of DLBS to the metro in different periods of a day is nearly zero, which means that over 50% of DLBS trips have very low probabilities of replacing metro. The reason is that only when the trip distance using DLBS is over 1.5 km, DLBS has a noticeable probability of replacing metro as demonstrated in Fig. 2a. Over 50% of trips using DLBS have a trip distance of fewer than 1.5 km, as demonstrated in Fig. 2a. Many places are not directly connected by metro systems, especially in the rural areas of Shanghai. However, if the origin and destination of a long-distance trip (at least over 2 km) are directly connected by metro systems and near metro stations, the travelers are very likely to choose metro if DLBS were not to exist (i.e., the points with high probability in Fig. 6d) since the metro system is much more reliable and faster as compared to taking buses, and cheaper than using taxi in Shanghai. These are the reasons for the observed patterns of the substitution rates of DLBS to the metro in Fig. 6d.

More importantly, Figs. 5 and 6 indicate large variances in the substitution rates of DLBS to a transport mode in spatial and

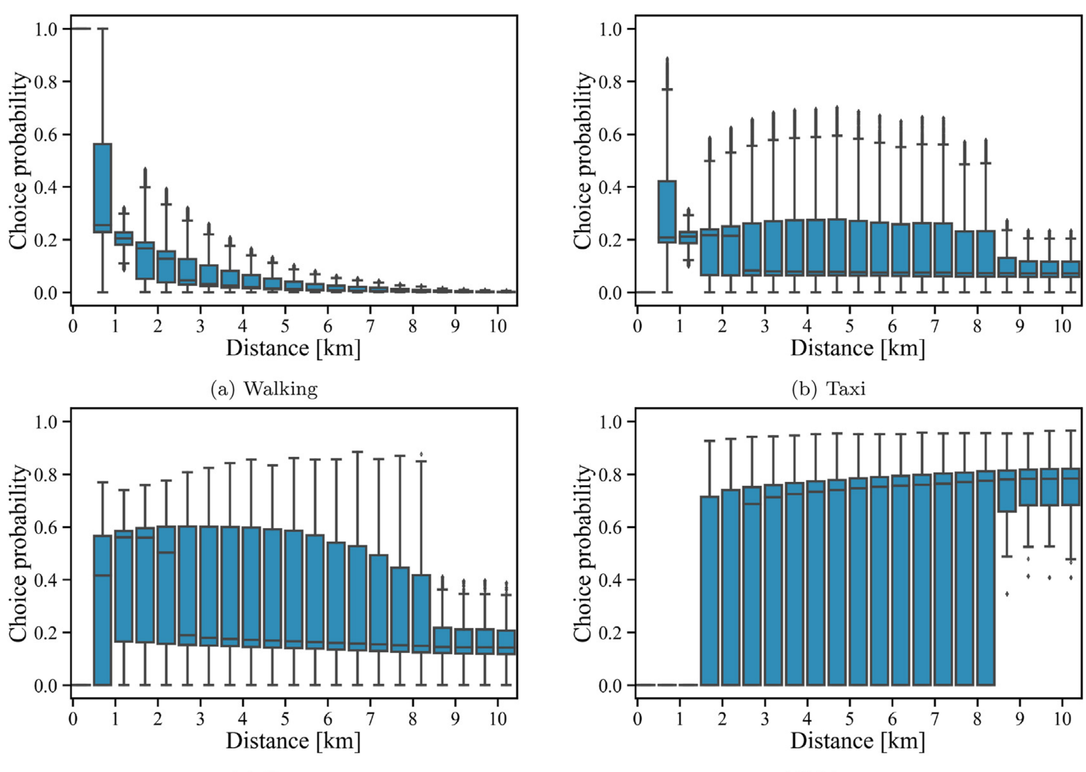


Fig. 5. Substitution rates of DLBS to different transport modes for different trip distances. The data are grouped with a distance interval of 500 m. The black line inside the orange box is the median value. The upper and lower bound of the orange box are the third quartile and first quartile.

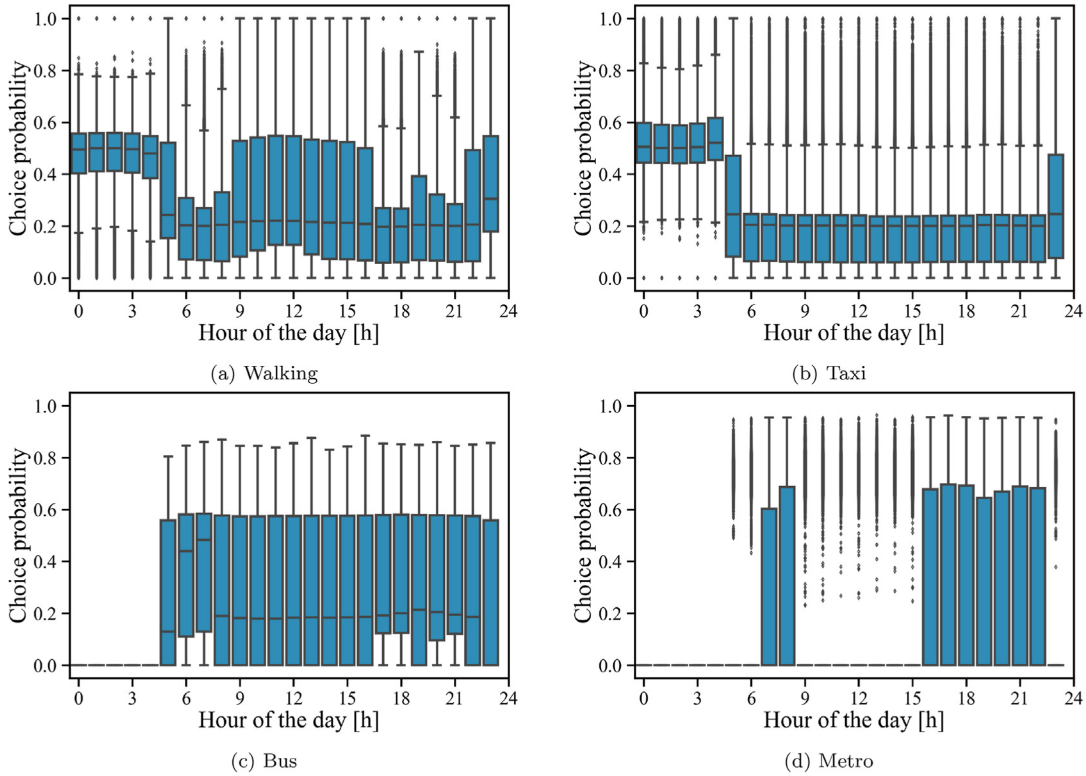


Fig. 6. Substitution rates of DLBS to different transport modes in different periods of a day.

temporal dimensions. For instance, the substitution of DLBS to the bus is zero at 3:00 a.m. but noticeable in the daytime. For trips with the same distances and departure time, the substitution rate of DLBS to a particular transport mode still presents large variances. For instance, the substitution rate of DLBS to bus in a trip distance of 2 km could range from 0 to 0.9. The probability of choosing a transport mode is highly dependent on the availability and superiority or inferiority of the option as compared to other options in terms of level-of-service variables such as cost and travel time. For a specific trip, the attributes of possible alternative transport modes are determined by the transport network (e.g., road structure and transit network) and departure time (e.g., the travel time of the bus is related to the match of departure time and bus schedule). These lead to large divergences in travelers' probability of choosing a specific transport mode in different urban contexts, even though the trips have the same distance, purposes, and departure times. Therefore, it is necessary to consider the particular travel contexts for a specific trip to estimate the substitution rate of DLBS to different transport modes. The results confirm the superiority of our proposed method in contrast to previous work. We improve the analysis accuracy to trip level. Our approach could address the variances in the substitution rate of a transport mode with full considerations of the available options and their attributes for a specific trip.

5.2. Environmental influences of DLBS

The environmental influences of DLBS are analyzed from the per-trip, overall, and spatiotemporal perspectives. Fig. 7 illustrates the statistical distribution of reduced GHG emissions from bike-sharing trips. The results indicate noticeable variance in the reduced GHG emissions across different bike-sharing trips. The amount of reduced GHG emissions from a bike-sharing trip is related to the substituted transport mode and trip characteristics (e.g., distance), which essentially present considerable heterogeneities in the spatiotemporal dimensions. Therefore, the notable differences in GHG emissions across different bike-sharing trips are logical. Interestingly, 35.26% of bike-sharing trips have negative values in the GHG emission reductions, indicating these DLBS trips increase GHG emissions. The reason is that some bike-sharing trips would be replaced by walking if there were not DLBS and the GHG emission of walking is zero. However, the GHG emission reductions for most bike-sharing trips using DLBS are positive, denoting a reduction in GHG emissions due to using DLBS for the trip. On average, a bike-sharing trip could reduce about 80.77 g CO_2-eq GHG emissions. The estimated GHG emission per trip is much less than results about docked bike-sharing systems in cities of the USA (ranging from 357 to 581 g CO_2-eq per trip) reported by Kou et al.

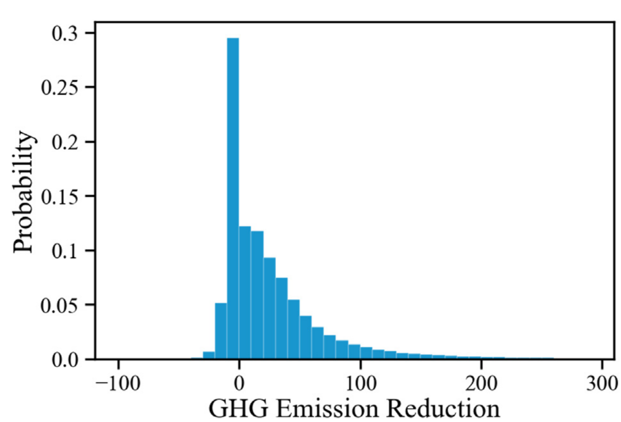


Fig. 7. The distribution of GHG emission reduction (g CO-eq) per trip.

(2020). The differences may be ascribed to the modeling methods and the investigated city contexts. Our method considers the detailed travel contexts of each recorded bike-sharing trip, which is much more accurate in the substituted mode by bike-sharing systems and thus more superior in assessing the GHG emission reduction as compared to Kou et al. (2020). At the same time, the city contexts in terms of road structure, transit network and bike-sharing system configurations, are different in our used data as compared to those in Kou et al. (2020). These will all lead to the differences in substituted transport modes by DLBS and thus the estimated GHG emission reductions at the per-trip and aggregated levels. The average daily ridership of DLBS in our dataset is 1,663,091, so the estimated GHG emission reduction for one day and one year is 134.33 t and 49,030.63 t CO_2-eq, respectively. Our dataset covers all the bikes from Mobike company, which were about 42% of all sharing bikes of all companies in Shanghai (Huang, 2018). It could be deduced that the environmental benefit from DLBS in Shanghai in terms of reducing annual GHG emissions is 116,739.58 t CO_2-eq. A typical gasoline light-duty passenger vehicle emits about 4.6 t CO_2-eq of GHG emissions per year (EPA, 2018). Therefore, the estimated GHG reductions from DLBS in Shanghai are equal to the GHG emissions of 25,378 passenger cars. This indicates that the operation of 24 bikes of DLBS in the contexts of Shanghai could compensate for the GHG emissions produced by a typical gasolin$_2$e passenger. The results reveal that the environmental benefits of DLBS are immense from the perspective of reducing GHG emissions. DLBS, as a shared mobility system, can not only improve the travel efficiency in terms of reducing travel time for short-distance trips but also contribute to reducing transport emission as well as per the estimated results, which is pronounced merit in the era of climate change.

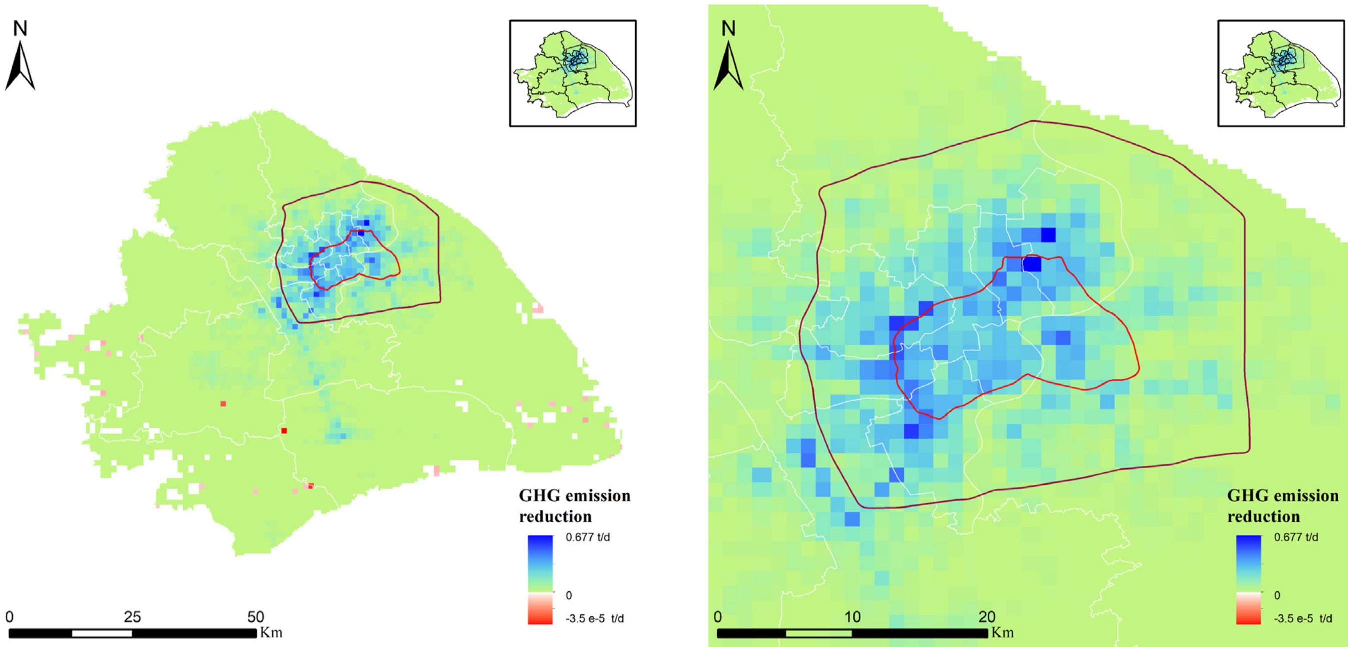
From the temporal perspective, Table 6 displays the reduced GHG emission per day across the studied period. Differences are observed in the daily overall GHG emission reduction between weekends and workdays. However, the average GHG emission reductions per trip across weekends and workdays show no differences. The differences in daily overall GHG emission reduction may be mainly ascribed to the ridership on different days. The ridership of DLBS on working days is larger than that in weekends, as displayed in Fig. 2c.

From the spatial perspective, Fig. 8 demonstrates the spatial distribution of daily aggregated GHG emission reductions due to DLBS in all AZs. Fig. 8b illustrates the GHG emission reduction in the AZs located inside the out-ring circle (i.e., the purple line), most of which are urban areas. The areas outside the out-ring circle are mostly suburban or rural areas of Shanghai. The GHG emission reductions from DLBS in urban areas are much larger than those in rural areas. The daily aggregated GHG emission reductions in AZs show a radial pattern. The AZs near the city center have comparatively higher environmental benefits from DLBS. The aggregated GHG emission reductions from DLBS in an AZ are strongly related to three aspects: substituted transport mode, trip distances, and the ridership of using DLBS. The higher overall GHG emission reductions in the central areas are probably due to the larger DLBS ridership in these areas as compared to rural areas. More importantly, the results in Fig. 8b explicitly elucidate the significant variances in GHG emissions reductions from DLBS in different urban contexts. The AZs with high GHG emission reductions are mainly located in Yangpu, Hongkou, Jing'an, Huangpu, Putuo, Changning, and Xuhui districts. Table 7 summarizes the environmental benefits from DLBS of each administrative district in Shanghai. The districts such as Huangpu and Hongkou have much more considerable GHG emission reductions per unit area. The possible reason is that high intensities of commercial and residential land use produce ridership of DLBS in these areas. The AZs that are far from the city center mostly have fewer GHG emission reductions due to DLBS as compared to those near to city center. The potential explanation is that the DLBS usage in these areas is comparatively small. We observe some (even very few) AZs present increased GHG emissions due to DLBS, which are marked by red in Fig. 9. The reason should be that the DLBS mainly replaces walking in these areas (e.g., in a logistic park). If a bike-sharing trip substitutes walking, it actually leads to increased GHG emissions (see Fig. 9).

Fig. 9 further displays the spatial distribution of per-trip GHG emission reduction. Again, the results reveal remarkable spatial variances in the per-trip GHG emission reduction. The average reduced GHG emission per trip in rural areas is generally higher than that in urban areas, which differs from the findings in the overall GHG emission reductions in AZs. The per-trip GHG emission reduction in an AZ is influenced by the replaced transport modes by DLBS and trip characteristics (e.g., average distance). The DLBS in suburban or rural areas is more likely to be used for relatively long trips and has a high probability of substituting the taxi due to lacking convenient public transit services and low land-use intensity. These will result in more GHG emission reductions per bike-sharing trip, in contrast to DLBS trips in central areas. Urban areas have better access to public transit and convenient accessibility to different services in a short distance. Thus, the DLBS in urban areas has a higher probability of replacing public transport (i.e., fewer GHG emission reductions as compared to replacing taxi) and is used for shorter trips as compared to rural areas, resulting in less GHG emission reduction per trip.

Table 6
GHG emission reduction in different days.

Date	Overall GHG emission reduction (t CO_2-eq)	Ridership	Average GHG emission reduction per trip (g CO_2-eq)
2018-08-26 (Sunday)	100.633	1251175	80.431
2018-08-27 (Monday)	146.754	1816128	80.806
2018-08-28 (Tuesday)	148.460	1836793	80.826
2018-08-29 (Wednesday)	147.044	1824887	80.577
2018-08-30 (Thursday)	148.027	1836778	80.590
2018-08-31 (Friday)	149.028	1855136	80.332
2018-09-01 (Saturday)	102.452	1290307	79.401
2018-09-02 (Sunday)	103.384	1309216	78.966
2018-09-03 (Monday)	130.415	1623008	80.354
2018-09-04 (Tuesday)	154.424	1897543	81.381
2018-09-05 (Wednesday)	157.588	1930774	81.619
2018-09-06 (Thursday)	154.745	1910511	80.997
2018-09-07 (Friday)	100.598	1217393	82.634
2018-09-08 (Saturday)	137.075	1683627	81.417



(a) For the study area (b) For the central area

Fig. 8. Spatial distribution of aggregated daily reduced GHG emissions.

Table 7
Daily GHG emission reductions due to DLBS in administrative districts.

District	Area (km^2)	Population (k)	Population density (k/km^2)	Overall CO_2-eq (t)	per area CO_2-eq (kg/km^2)
Huangpu	20.50	650.80	31.75	4.84	236.32
Hongkou	23.45	710.91	30.32	6.35	270.73
Jingan	37.37	1066.20	28.53	8.10	216.85
Putuo	55.53	1284.70	23.14	10.43	187.88
Yangpu	60.61	1312.70	21.66	10.88	179.50
Xuhui	54.93	1088.30	19.81	11.40	207.57
Changning	38.30	693.60	18.11	7.46	194.71
Minhang	372.56	2549.30	6.84	18.83	50.55
Baoshan	293.71	1904.80	6.49	7.90	26.89
Pudong	1210.00	5501.00	4.55	25.08	20.72
Jiading	462.20	1588.90	3.44	5.71	12.35
Songjiang	604.67	1764.80	2.92	8.29	13.72
Qingpu	676.00	1219.00	1.80	1.55	2.30
Fengxian	720.44	1155.30	1.60	6.56	9.11
Jinshan	613.00	798.00	1.30	0.89	1.46

5.3. Associations of built environment with the environmental benefits of DLBS

The above results indicate substantial variances in the GHG emission reductions from DLBS in different urban contexts, which imply the correlations of the environmental benefits from DLBS with built environments. Hence, we examine the potential associations between the built environment factors and the reduced GHG emission in an AZ. All the examined factors are listed in Table 5. To avoid the biases due to multicollinearity among explanatory variables, we exclude the explanatory variables with the variable inflation factor of larger than five. Besides, we select the optimal model according to the corrected Akaike Information Criterion and the significance level of the explanatory variables. The final results are summarized in Table 8. The adjusted R^2 of the model is 0.771, denoting that the model could explain 77.1% of variances in the daily aggregated GHG emission across different AZs. The coefficients of the remaining explanatory variables are all significant at the 95% confidence level.

The aggregated GHG emission reductions due to DLBS in an AZ depend on three aspects: substituted transport mode by DLBS, trip distances, and the ridership of using DLBS. Built environment factors influencing the three aspects would thus affect the aggregated GHG emission reduction in an AZ. Particularly, some factors may influence several aspects and may have compound effects on the aggregated GHG emission reductions from DLBS. For instance, the road density of different road categories influences both the substituted transport modes and trip distance of bike-sharing trips. The results indicate population density (PD) and employment density (ED) are positively related to the daily GHG emission reductions, denoting AZs with a higher population or employment density benefit more from DLBS. Higher PD and ED in an AZ mean more usage demand of DLBS and larger daily ridership, which are expected to create more GHG emission reductions from DLBS. For

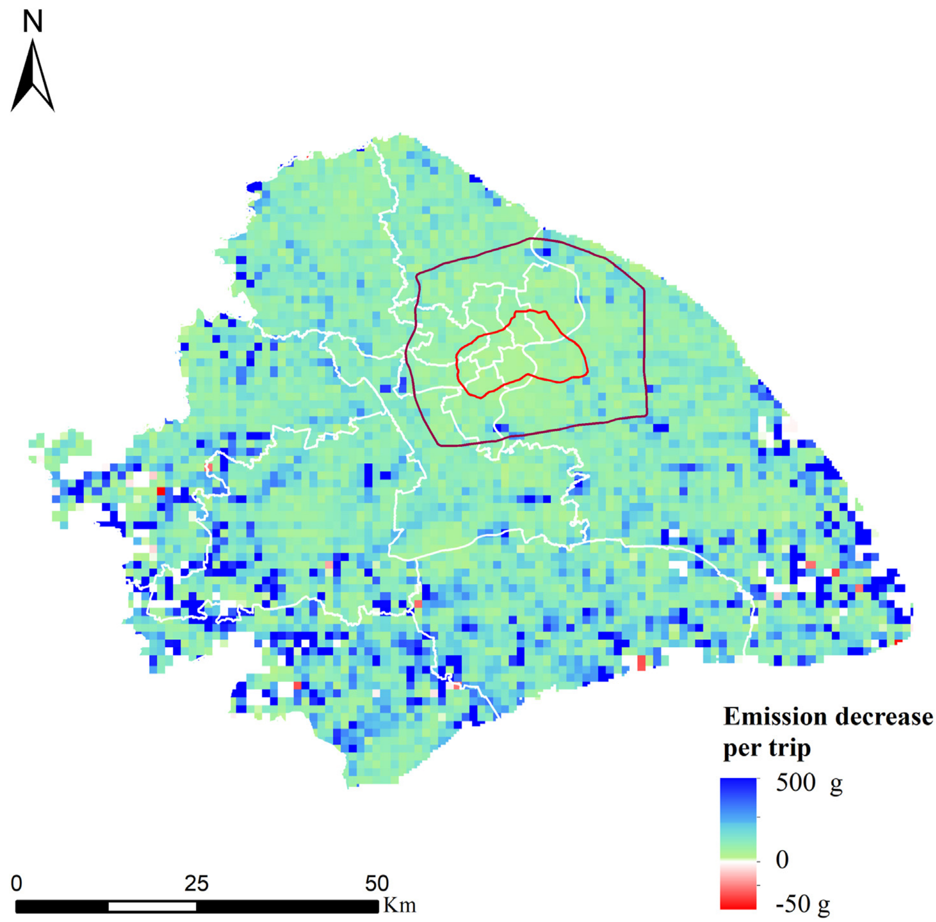


Fig. 9. Spatial distribution of per-trip GHG emission reduction.

Table 8
The influences of built environment factors on the environmental benefits of DLBS.

Variables	Coef.	Std. Err.	t	P	VIF
Constant	0.259	0.004	59.148	0.000*	0.000
Density					
PD	0.229	0.008	30.007	0.000**	3.034
ED	0.210	0.007	29.723	0.000**	2.618
Diversity					
CLUR	−0.019	0.005	−4.277	0.000**	1.077
Design					
MD	0.056	0.004	12.579	0.000**	1.032
MRD	0.060	0.006	9.824	0.000**	1.944
BRD	−0.014	0.005	−2.767	0.006**	1.263
BLD	0.028	0.005	6.036	0.000**	1.116
Destination					
EFD	0.099	0.006	17.501	0.000**	1.679
PSD	−0.011	0.005	−2.149	0.032*	1.313
Transit					
ARSubway	0.125	0.006	20.996	0.000**	1.845
ARBus	−0.046	0.007	−6.887	0.000**	2.377

R^2: 0.772.
Adjusted R^2: 0.771.
** and * Significant at the 0.01 and 0.05 level, respectively.

the factors regarding diversity, only commercial land use ratio (CLUR) shows a significant influence on the environmental benefit of DLBS. AZs with higher CLUR present fewer GHG emission reductions. The commercial areas in Shanghai are generally surrounded by public transit and parking facilities. DLBS in areas with high CLUR may mainly serve as the connection tools from transit stations or parking lots to the final destinations. In such cases, the bike-sharing trips are short-distance and are likely to substitute walking rather than automated transport modes. These will result in fewer GHG emission reductions in AZs with higher CLUR.

As for explanatory variables about design, the motorway density (MD), motorized road density (MRD), and bicycling lane density (BLD) have significant and positive relations with the daily aggregated GHG emission reduction in AZs. These manifest AZs with higher MD, MRD, and BLD have more GHG emission reductions from DLBS. Higher MD and MRD in an AZ imply that travelers have a higher probability of using automated modes for traveling rather than walking if DLBS did not exist. Therefore, the DLBS in these areas are more likely to replace trips of automated modes (e.g., car and bus), and thus have higher GHG emission reduction due to DLBS. AZs with more BLD are more friendly for using DLBS and could increase both ridership and substitutions of DLBS to automated modes, which lead to higher environmental benefits in AZs with higher BLD. However, the branch road density (BRD) is found to be negatively related to the GHG emission reductions from DLBS. The potential explanation is that the branch road is friendly for walking. The DLBS in AZs with high BRD may mainly replace walking. In terms of variables about destination, AZs with a higher education facility density (EFD) have higher environmental benefits from DLBS, while the park and square density (PSD) present a negative impact on the GHG emission reduction. DLBS is a prevalent tool for students, especially college students, to get access to surrounding services in Shanghai. This may be the reason for higher GHG emission reduction in AZs with higher EFD. The negative influence of PSD is because DLBS is generally prohibited inside parks and squares and thus less usage of DLBS in AZs with higher PSD. As for variables related to transit stations, ARMetro is positively related to GHG emission reductions. Higher ARMetro means more convenience to use metro systems. As a popular feeder to metro stations, DLBS is expected to create more GHG emission reduction by replacing other feeder choices such as bus and taxi. However, the ARBus is negatively linked to the GHG emission reductions from DLBS. The convenience of using buses (i.e., higher ARBus) would reduce not only the amount of bike-sharing trips but also the probability of using a taxi for the trip if DLBS were not available. In short, the results of the above analysis reveal that the influences of built environment factors on the environmental benefits from DLBS. The quantitative estimation provides insights into how the urban contexts could influence the GHG emission reductions from DLBS. The results could be utilized for evaluating the societal benefits of DLBS as per the built environment in different urban contexts, for the planning and cost-benefit analysis regarding DLBS.

6. Conclusions and future work

The environmental benefit of bike-sharing systems is one of the main motivations for developing them in urban contexts. However, very few studies quantitatively and accurately assessed the environmental influences of DLBS. This study proposes a novel framework for assessing the environmental benefit of bike-sharing systems leveraging passive transaction record data and trip-specific mode substitution estimations. The proposed approach can decipher how the DLBS replaces other transport modes for a specific trip at a high resolution, and estimate the GHG emission reduction due to the DLBS at the resolution of trip level. Utilizing the proposed approach, we conduct an empirical analysis to empirically reveal the environmental influences of DLBS in Shanghai of China from both per-trip and aggregated perspectives. The main contributions of this study could be summarized as follows:

- A new framework for evaluating the environmental influences of DLBS at the resolution of the trip level is developed and used for empirical analysis.
- Our empirical analysis in Shanghai reveals that the substitution rates of DLBS to different transport modes have substantial variances in both spatial and temporal dimensions, and highly depend on travel contexts. For trips with the same distance and departure time, the substitution rates of DLBS to a transport mode show considerable differences. These highlight the necessity to estimate the trip-specific substitution rates of DLBS to different transport modes in assessing the environmental influences of DLBS, rather than using aggregated-level methods in the existing literature.
- The estimated GHG emission of a bike-sharing trip using DLBS in Shanghai is 80.77 g CO_2-eq on average, as compared to the scenarios without DLBS. The annual GHG emission reductions are estimated to be 116,739.59 t CO_2-eq in Shanghai, which is very pronounced and equal to the GHG emissions of over 25,378 typical gasoline vehicles. The results provide quantitative assessments concerning the environmental benefits of DLBS, which are crucial references in the development, planning, and policy-making concerning bike-sharing systems.
- Spatial heterogeneity exists in the environmental benefits of DLBS in urban contexts. The overall environmental benefits of DLBS are much larger in the center areas than in rural areas. However, the GHG emission reduction per bike-sharing trip in rural areas is much larger than that in central regions. The built environments are identified to have significant influences on the GHG emission reductions from DLBS. More specifically, built environment factors, including population density, employment density, motorway road density, motorized road density, bicycle lane density, education facilities, and accessibility to metro stations, are significantly and positively related to more GHG emission reductions due to DLBS. Commercial land use ratio, park and square density, and accessibility to bus stations have negative associations with the aggregated GHG emissions from DLBS.

Although this study makes a novel contribution to the methods and empirical analysis concerning quantitative assessment of environmental influences of DLBS, there are still limitations that could be further improved and investigated in the future. Notwithstanding, our proposed method can consider all the alternative transport modes as long as corresponding data are available. In our analysis, we do not consider the substitution of DLBS to private cars. The reason is that it is impossible to know whether a user could use private transport modes (e.g., private electric bike and private vehicle) for a specific trip, merely based on transaction data of DLBS. However, the substitution percentages of DLBS to private cars are very low (less than 3%) in Shanghai (Wang, 2019), which would not make a difference in the empirical analysis of Shanghai. Nonetheless, the situations in other cities such as small-size cities in Europe may be divergent as the substitution of bicycling to private cars in these cities. It is more accurate to consider the possible availability of electric bikes and private cars based on other data resources to precisely estimate the replaced transport mode by bike-sharing systems in various travel contexts. Moreover, a more comprehensive and detailed life cycle assessment for GHG emissions of different transportation modes can be conducted to improve the estimation of GHG emissions reductions. For instance, other aspects of DLBS, such as rebalancing the distributions of bikes, also contribute to the overall GHG emissions of DLBS, which are not fully considered in the present study due to lacking of corresponding data. Lastly, although the dataset used in our empirical covered over 40% operating sharing bikes in Shanghai over the studied period, it is more accurate to conduct analysis using the proposed method based on data of all sharing bikes if such data were available.

Credit authorship contribution statement

Aoyong Li: Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing. Kun Gao: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. Pengxiang Zhao: Resources, Writing - review & editing. Xiaobo Qu: Conceptualization, Writing - review & editing, Validation, Supervision. Kay W. Axhausen: Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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